

The Relationship between Education and Occupation Using Fully and Partially Latent Models

Faisal G. Khamis*, Muna F. Hanoon and Abdelhafid Belarbi

Faculty of Economics and Administrative Sciences, Al-Zaytoonah University of Jordan, Amman, Jordan

ABSTRACT

Several studies have been carried out to examine the association between education and occupation. These studies were useful for the purpose of intervention and policy making. In this study we examined the relationship between education factor, which includes three indicators: the percentages of population who achieved (primary, secondary and tertiary) and occupation factor (CLASS1, CLASS2 and CLASS3) using fully and partially latent models. The data were collected from the information of 81 districts based on the census conducted in peninsular Malaysia in 1995. The goodness of fit indexes for assumed models were examined. We didn't find significant relationship between educational achievement and occupation factor. This study was composed for a number of path-diagrams to create a picture for socioeconomic status in Malaysia.

Keywords: Occupation; Education; Relationship; Fully latent models; MIMIC models

1. Introduction

The education of people in the community is potentially important because it may influence society in ways that affect everyone. For example, most hospitals and health centers in Malaysia were public, with financing from national sources, and were subjected to national quality regulations, but when many local people are well educated, it is perhaps easier to recruit qualified health for all the members of the family. Besides, education was a major determinant of income [21]. A low relative education was at least linked with low relative income. Blane, Brunner and Wilkinson [6] stated that men and women with low educational attainment were the least likely or slowest to respond to the messages of health education. The results of Ross and Wu [27] demonstrated a positive association between education and health and help explain why the association exists. (1) Compared to the poorly educated,

* Corresponding author: faisal_alshamari@yahoo.com

well educated respondents were less likely to be unemployed, were more likely to work full time, to have fulfilling, subjectively rewarding jobs, high incomes and low economic hardship. (2) The well educated reported a greater sense of control over their lives and their health, and they had higher levels of social support. Duper [12] used regression models to examine how education relates to low income and unemployment.

Anderson [1] stated that the integration of work-experience education within the curriculum helps to prepare the student for a practical, productive life, which means that interpersonal skills can be developed through student-teacher-employer relationships. Also, work-experience education program guides the student into an awareness of his/her responsibilities as a citizen. Accumulating evidence suggests that a highly qualified workforce contributes substantially to a nation's economic competitiveness, particularly when a large share of the workforce has acquired skills and knowledge through higher education, and these findings applied to states as well as nations, where US states that improved opportunities for education and training beyond high school advanced their residents' employment prospects and the competitiveness of their overall workforce [31]. The World Development Report [33] suggested that although curricula and teaching methods had remained largely unchanged in developing countries over the years, employers were increasingly demanding strong thinking, communication, and entrepreneurial skills largely unmet by educational systems in the developing and transition economics.

The literature on human capital accumulation indicated that high quality education at the primary level generates the highest returns, both at the primary level and all levels thereafter in both developing and transition countries. Fasih [13] stated that, if the relationship of education and earnings is convex or linear, then expanding enrollment only at lower levels of education will not raise earnings substantially, and consequently not prove to be an effective means of helping people out of poverty. In countries such as Malaysia where there were large disparities in the quality of education between the rich and the poor, and where individuals were systematically sorted into high-quality schools by wealth, the poor were attained fewer skills for the same "quantity" of education. The policy option in such a case would be to counter the sorting process through the provision of choice of better schooling through, for example, school vouchers or better-quality publicly funded private schools for the poor [2, 3]. When Bertrand [5] examined the education in terms of its usefulness as a preparation for employment, he stated that the theoretical analysis of education contribution to the productivity of labor and the methods used to forecast the quantitative needed for the economy gave rise to considerable controversy and seemed to provide no more than very general indications. Also, Bertrand found that economy needed to provide enough jobs to meet demand, which became an increasingly unlikely prospect in many countries and would call for some rethinking of education's role in this field. So the purpose of this research is to provide some implications for the policy makers regarding the

increasing opportunities for all members in the community to enhance their levels of education. This increase will probably increase the opportunities of getting a job and also enhance the levels of jobs with better environment and salary. It is not easy to decide which way higher education ought to go. It is clear that the modern economy demands a higher proportion of highly qualified personnel, but it is difficult to say to what extent. Levin and Rumberger [22] stated that over-education stemmed from a more rapid increase in the number of university graduates was greater than offers of employment. The European trend towards extended study, for example, is certainly caused more by social demand than by the needs of the economy and will probably lead to frustration among young people, who will not always be able to find the high-level employment that they expect.

In this study, structural equation modeling (SEM) was used, where SEM was defined as hybrid model since it was a mixed system of equations between structural equation and measurement equations. There were many advantages of SEM technique making it applicable in many situations. First SEM technique has several flexible assumptions, such as allowing for correlations between independent variables, thus providing solution for multicollinearity problem in regression analysis. Second, SEM allows for the use of factor analysis to reduce the measurement error by having multiple indicators (manifest variables) per latent (factor) variable. Third, SEM has a structural graph of attraction because it provides graphical modeling interface. Fourth, SEM provides mechanism for testing overall model rather than testing each individual coefficient in the model, so that complex relationships can be easily identified and understood. Fifth, SEM has the ability to test models with multiple dependents. Sixth, SEM has the ability to model the mediating latent variables.

The SEM approach was convenient because it allows multiple measures of the same characteristic to be included in the model; this approach may reduce potential bias from measurement error in the observed variables [9]. SEM has characteristics which allow the results to be more informative compared to the more traditional applied multiple regression and path analysis techniques. Also, SEM allows a range of relations between variables to be recognized in the analysis compared to multiple regression analysis, and those relations can be recursive and non-recursive [29]. Thus, SEM provided the researcher with an opportunity to adopt a more holistic approach to model building.

2. Materials and methods

2.1 Data

The data were collected from the department of statistics [24] based on the census of 81 districts conducted in peninsular Malaysia. We must construct on the basis of the prior concept or statistical analyses, which particular *indicators* load on

each latent variable. More precisely, we constructed the following latent variables with their respective indicators:

Occupation factor: Occupation latent factor included three classes of occupation, starting from top to bottom in the income and social level were used as follows: CLASS1 included professional, administrative and managerial workers; CLASS2 included clerical workers and CLASS3 included sales and service workers. All classes were measured in percentages. These indicators described the type of occupation status for people living in the district.

Education factor: Education latent factor included three indicators: percentages of population who achieved (primary, secondary and tertiary) education. A strong public economy resulting from a high average education may allow more generosity with respect to social support, and high individual incomes may trigger the establishment of some smaller private health services. Another possibility is that a higher level of education may increase the chance that the individual has a well paid job in the advanced service sector, which may offer some health advantages. Education attainment may reflect a person's capacity to absorb new information and to act on it [25]. The focus was on education, which is readily available, often used, and theoretically meaningful indicator.

2.2 Analysis

Fully latent models: Fully latent models or SEM is an extension of standard regression models through which multivariate outcomes and latent variables can be modeled. SEM is more appropriate for this application than alternative causal modeling technique because they permit specification of "measurement models." SEM needs two types of models: the measurement model (outer model), which connects the manifest variables to the latent variables and the structural model (inner model), which connects latent variables between them. Slight to moderate departures from normality can be handled by the maximum likelihood (ML) method [26]. In the observed variables, we found slight departures from normality. ML estimates are quite robust to violation of normality assumption in the factor model [4, 18]. The causal variable is called exogenous variable, ξ , and the effect variable is called the endogenous variable, η . Unexplained variation is referred to as disturbance. The aim is to test the synthesized model of relations between the latent variables, where the structural equation model can be written as: $\eta = \mathbf{B}\eta + \mathbf{\Gamma}\xi + \zeta$. Vectors η and ξ are not observed, instead vectors \mathbf{y} and \mathbf{x} are observed, such that: measurement model for \mathbf{y} : $\mathbf{y} = \mathbf{\Lambda}_y\eta + \varepsilon$, and measurement model for \mathbf{x} : $\mathbf{x} = \mathbf{\Lambda}_x\xi + \delta$.

MIMIC or partially latent models: The term MIMIC stands for Multiple Indicators and Multiple Causes [19]. MIMIC model involves two types of models: the measurement model (outer model), which relates the indicators to the latent variables and the structural model (inner model), which explain the relationship between latents. The structural equation model is: $\eta = \mathbf{\Gamma}\mathbf{x} + \zeta$, and measurement

model for \mathbf{y} : $\mathbf{y} = \Lambda\boldsymbol{\eta} + \boldsymbol{\varepsilon}$, where \mathbf{y} is a $p \times 1$ vector of response variables, \mathbf{x} is a $q \times 1$ vector of predictors, $\boldsymbol{\eta}$ is an $m \times 1$ random vector of latent dependent, or endogenous variables, $\boldsymbol{\varepsilon}$ is a $p \times 1$ vector of measurement errors in \mathbf{y} , Λ is a $p \times m$ matrix of coefficients of the regression of \mathbf{y} on $\boldsymbol{\eta}$. The coefficients of Λ are the weights or factor loadings that relate the observed measures to the latents. The Γ is an $m \times q$ matrix of coefficients of the x -variables in the structural relationship. The elements of Γ represent direct causal effects of x -variables on η -variables. The ζ is an $m \times 1$ vector of random disturbances in the structural relationship between $\boldsymbol{\eta}$ and \mathbf{x} , where in this study: $p = 3$, $q = 3$ and $m = 1$. The random components in LISREL model were assumed to satisfy the following minimal assumptions: $\boldsymbol{\varepsilon}$ is uncorrelated with $\boldsymbol{\eta}$, ζ is uncorrelated with \mathbf{x} , and ζ and $\boldsymbol{\varepsilon}$ are mutually uncorrelated. The model is identified if there are two or more latents and each latent has at least two indicators [7, 20]. The models under study were identified since each of education and occupation latent variables included three indicators.

Parameter estimation: Parameter estimation was performed by ML estimation. The unknown parameters of the model were estimated so as to make the variances and covariances that were reproduced from the model in some sense close to the observed data. Obviously, a good model would allow very close approximation to the data. The proposed models are designed specifically to answer such questions as: Is the link between occupation and education myth or reality? From the previous studies, this link was reality in some countries but what about Malaysia?

Fit indexes: perhaps the most basic fit index is the likelihood ratio, which is sometimes called Chi-square (χ^2) in the SEM literature. The value of the χ^2 -statistic reflects the sample size and the value of the ML fitting function. The fitting function is the statistical criterion that ML attempts to minimize and is analogous to the least squares criterion of regression. For a particular model to be adequate, values of indexes that indicate absolute or relative proportions of the observed covariances explained by the model such as the Goodness-of-Fit Index (GFI), the Adjusted Goodness-of-Fit Index (AGFI), and Normed Fit Index (NFI) should be greater than 0.90 [7, 15]. Comparative fit index (CFI) indicates the proportion in the improvement of the overall fit of the researcher's model relative to a null model like NFI but may be less affected by sample size. CFI should be greater than 0.90 [20] or Hu and Bentler [17] endorsed stricter standards, pushing CFI to about 0.95. Another widely used index is the standardized Root Mean Squared Residual (SRMR), which is a standardized summary of the average covariance residuals. Covariance residuals are the differences between the observed and model-implied covariances. A favorable value of the SRMR is less than 0.10 [17]. Another measure based on statistical information theory is the Akaike Information Criterion (AIC). It is a comparative measure between models with different numbers of latents. AIC values closer to zero indicate better fit and greater parsimony [7, 15]. The parsimonious goodness-of-fit index (PGFI) modifies the GFI differently from the AGFI; where the AGFI's adjustment of the GFI is based on the degrees of freedom in the estimated

and null models. The PGFI is based on the parsimony of the estimated model [15], where this index varies between 0 and 1, with higher values indicating greater model parsimony. The Non-Normed Fit Index (NNFI) includes a correction for model complexity, much like the AGFI; a recommended value is 0.90 or greater [15]. The Root Mean Square Error of Approximation (RMSEA) value below or equal to 0.08 is deemed acceptable [15] or Hu and Bentler [17] pushes RMSEA values to smaller than 0.06 and they considered it greater than 0.10 as poor fit. RMSEA is a measure to assess how well a given model approximates the true model [7].

Path diagrams: A popular way to conceptualize a model is using a path diagram, which is a schematic drawing of the system (model) to be estimated. There are a few simple rules that assist in creating these diagrams. Ovals represented latent variables. Indicators were represented by rectangles. Directional relations were indicated using a single-headed arrow. The expression “a picture is worth a thousand words” is a very apt one for SEM. Researchers who used SEM technique often used path-diagrams to illustrate their hypotheses and summarize the results of the analysis. Figures 1 and 2 were shown a conceptualized path diagrams for the proposed models 1 and 2 respectively, explaining the parameters required to be estimated.

The sample design included two latent factors. The education factor, ζ , which constructed from three indicators, x_1 , x_2 , and x_3 , that represented three levels of education, primary, secondary and tertiary respectively. The occupation factor, η , which included also three indicators, y_1 , y_2 , and y_3 that represented CLASS1, CLASS2 and CLASS3 of occupation respectively. For model 1 the analysis included the following SEM model: $\eta = r\zeta + \varsigma$, $\mathbf{y} = \eta\Lambda_y + \boldsymbol{\varepsilon}$ and $\mathbf{x} = \zeta\Lambda_x + \boldsymbol{\delta}$, and for model 2: $\eta = \Gamma\mathbf{x} + \varsigma$, and $\mathbf{y} = \eta\Lambda_y + \boldsymbol{\varepsilon}$. Where, Λ_y and Λ_x represented a vector of factor loadings of order 3×1 ; $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$ represented a vector of measurement errors of order 3×1 for vectors \mathbf{y} and \mathbf{x} respectively; Γ represented a vector of parameters required to be estimated of order 1×3 .

3. Results

Every application of SEM should provide at least the following information: a clear and complete specification of models and variables, including a clear listing of the indicators of each latent; a clear statement of the type of data analyzed, with presentation of the sample correlation or covariance matrix; specification of the software and method of estimation; and complete results [26]. Table 1 showed Pearson correlation matrix, mean, and standard deviation for each indicator. As shown in Table 2, we provided several indexes of goodness of fit, allowing for a detailed evaluation of the adequacy of the fitted models. The simplest gauge of how well the model fits the data would be to inspect the residual matrix [14]. The acceptable range of residual values was one in 20 standardized residuals exceeding ± 2.58 strictly by chance [15]. All models have not resulted in standardized residuals

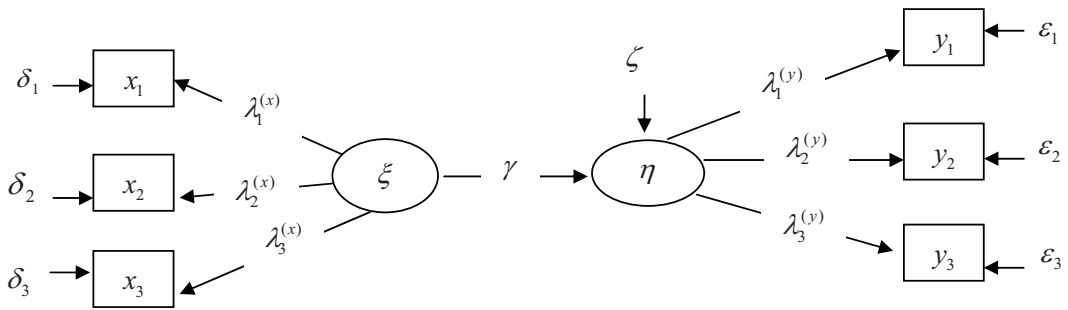


Figure 1. Conceptualized path-diagram for model 1 represents all variables.

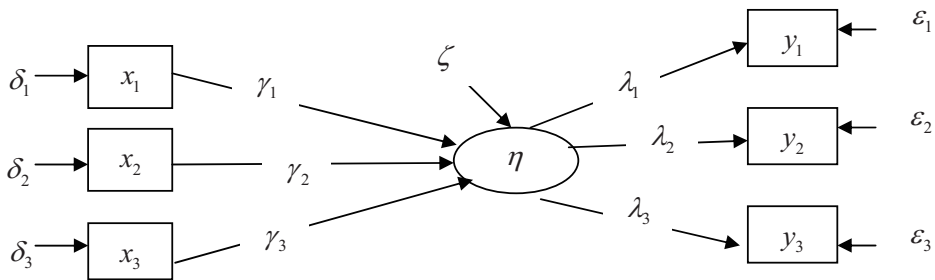


Figure 2. Conceptualized path-diagram for model 2 represents all variables.

exceed the threshold value, and most of them were found close to zero, indicating high correspondence between elements of the implied covariances matrix of vector, $\mathbf{z} = (\mathbf{y}, \mathbf{x})$, denoted as Σ and the sample covariance matrix, \mathbf{S} . For assessing the fitted model, a model was considered adequate if the p -value was greater than 0.05, as 0.05 significance level was recommended as the minimum acceptance level for the proposed model [15]. It was found that p -value for the fitted models was found greater than 0.05 as shown in Table 2, indicating that the proposed models were acceptable or adequate in interpreting the relationship between education and occupation.

Bollen's incremental fit-index values were examined as these are least biased due to non-normality of variables and they were found most of them close to 0.95. Figures 3 and 4 explained the estimated parameters of fitted models 1 and 2 respectively. Model 1 and model 2 provided an excellent fit to the observed data as shown in Table 2, where for model 1 with $(\chi^2(8) = 6.99, p\text{-value} = 0.54)$ and for model 2 $(\chi^2(6) = 6.23, p\text{-value} = 0.40)$. The estimated effect of education factor (labeled in Figure 3 as *educ_ach*) on occupation factor (labeled in Figure 3 as *occupati*) was found not significant with $(\hat{\gamma} = -0.12, t = -1.14)$ based on fitted model 1. The estimated effects of education indicators on occupation factor were all found not significant with $(\hat{\gamma}_1 = -0.02, t = -0.51; \hat{\gamma}_2 = 0.00, t = -0.08; \text{ and } \hat{\gamma}_3 = 0.01, t = 0.09)$ respectively. Model

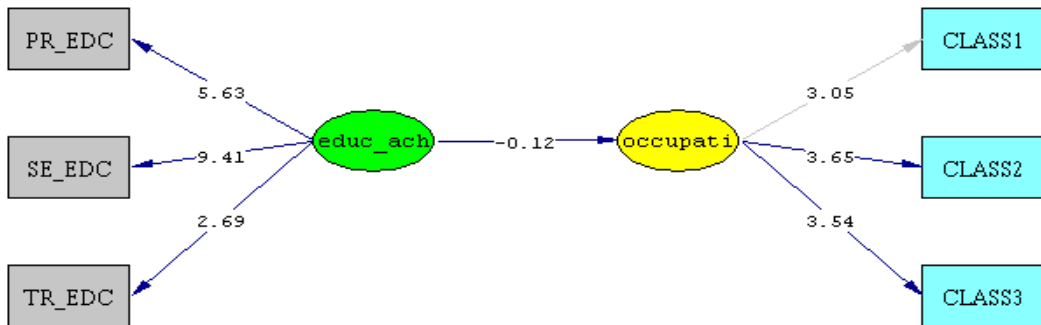


Figure 3. Path diagram shows the results of fitted model 1.

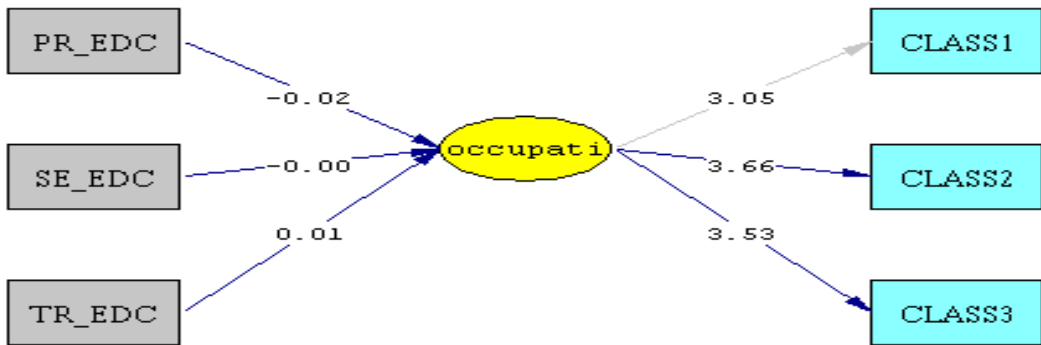


Figure 4. Path diagram shows the results of fitted model 2.

1 and model 2 were considered non-nested models. Non-nested models differ in number of latent factors or indicators. We can use AIC measure to compare between non-nested models. Given two non-nested models, the one with the lowest AIC was preferred [20]. However, model 1 was slightly better than model 2 because its AIC was found somewhat less than AIC of model 2 as shown in Table 2.

4. Discussion

The role of this study was to review what was known about the role of education in improving the finding for high level of job opportunities in both salary and social position. This subject was studied using several techniques and in this study structural equation modeling was used because we had several indicators for such latent factor. Bollen et al. [8] argued that the latent factor approach had two advantages. First, this approach permits the integration of a range of measures or indicators of socioeconomic status (SES), thus avoiding the problems with choosing a

Table 1. Pearson correlation matrix, Mean, and Standard Deviation (SD) for each variable.

Variables	y_1	y_2	y_3	x_1	x_2	x_3	Mean	SD
CLASS1, y_1	1.00						10.07	3.30
CLASS2, y_2	0.88**	1.00					6.82	3.84
CLASS3, y_3	0.66**	0.68**	1.00				18.36	4.98
PR_EDC, x_1	-0.15	-0.16	-0.08	1.00			68.54	6.50
SE_EDC, x_2	-0.14	-0.14	-0.14	0.91**	1.00		45.80	8.94
TR_EDC, x_3	-0.12	-0.10	-0.11	0.71**	0.86**	1.00	6.17	3.28

Note: ** Correlation is significant at the 0.01 level (2-tailed).

Table 2. Comparison between the proposed models using fit indexes.

Fit-indexes	Model 1	Model 2
<i>Absolute-Fit measures</i>		
χ^2 -statistic(p -value)	6.99(0.54)	6.23(0.40)
$d.f$	8	6
GFI	0.97	0.98
SRMR	0.03	0.01
RMSEA	0.000	0.001
<i>Incremental-Fit measures</i>		
CFI	1.00	1.00
AGFI	0.93	0.91
NFI	0.98	0.98
NNFI	1.00	1.00
<i>Parsimonious-Fit measures</i>		
PGFI	0.37	0.28
AIC	32.81	36.04

Note: χ^2 -statistic = Likelihood-Ratio Chi-Square Statistic, GFI = Goodness-of-Fit Index, SRMR = Standardized Root Mean Square Residual, RMSEA = Root Mean Square Error of Approximation, CFI = Comparative fit index, AGFI = Adjusted Goodness-of-Fit Index, NFI = Normed Fit Index, NNFI = Non-Normed Fit Index (An old name for the NNFI is the Tucker-Lewis Index TLI), PGFI = Parsimonious Goodness-of-Fit Index, AIC = Akaike Information Criterion.

single indicator. Secondly, this method allows greater control for measurement error. Ross and Wu [27] concluded that high educational attainment proves health directly, and it improves health indirectly through work and economic conditions. In Pakistan for example, most studies analyzed the determinants of enrollment in school had found the association between household income and girl’s enrollment in school to be positive and statistically significant [16, 32]. But the question in this paper is: what is the effect of education achievement on prosperity of the community represented by the occupation factor? Improvements to the quality and efficiency of basic

education are urgently needed, in both developing and transition countries such as Malaysia. Therefore, policies are required to focus on (i) improving the efficiency of educational spending, so that the development of core skills does not require more years, and (ii) adapting the curriculum of basic as well as post basic education to develop the skills increasingly in demand in the global labor market: critical thinking, problem solving, and behavioral (that is, noncognitive) skills, as well as skills in information technology. If improving the quality and quantity of skills was part of any educational package, this doesn't mean the package should succeed unless the issue of job creation was addressed. The supply of adequate jobs for the labor market is important for any policy maker. However, it is not simply whether an adequate number of jobs exist, but whether these jobs are of adequate quality. For example, subsidies in tertiary education need to be accompanied by the creation of an environment conducive to investment and technological progress. In the absence of such an environment, countries will find their population emigrating for better opportunities and governments will need to continue subsidizing education to compensate for weak effective demand. Different countries at different levels of economic development had diverse requirements for education [13]. For example, a study by De-Ferranti et al. [11] suggested that whereas East Asian countries might benefit from more secondary school graduates to fill their skill needs gap, Latin American countries, because of their wealth of natural resources, would benefit from more experts in manufacturing processes and more tertiary education graduates. It is essential to invest in quality early childhood education because the suggestion is: if the investment is made in developing the cognitive skills of children, the better the long-term impacts are for learning, skills development, and labor market outcomes. In a perfectly competitive labor market, skills such as motivation and ability may have higher value, thus people with higher ability may reap higher returns. From an education policy maker's point of view, this finding supports the importance of noncognitive skill development in schools and the education system as a whole. Also, the country context needs to be considered before recommending policy changes because decreasing returns from getting education could be the result of wage distortions caused by labor market rigidities. Expansion of higher education with no relation to job openings, and the resulting graduate unemployment, is the main cause of the brain drain which affects many of the developing countries, constituting a serious waste of resources. Rwomire [28] stresses the fact that the development of education has simply given rise to the replacement of a poorly-educated work force by one with a higher level of education. The number of jobs does not increase as quickly as the number of graduates, and therefore the higher level of instruction had been of no benefit to the economy. Von Borstel [30] examined the conditions for the success of a form of education that included productive work, where productive work is subordinate to school curricula and responds to the aims of education. However, most probably there was a lack in productive work in the school curricula in most of districts' schools in Malaysia in 1995. Also, we encouraged to

offer job opportunities for young people, which enabled them to avoid leaving school early and this means that those people will face difficulties to get better jobs either in income level, social level or both because they left their school early. As Chung [10] pointed out, in many developing countries, the majority of the population cannot get regular jobs in the modern sector and a large percentage were condemned to remain in a state of long-term under-employment. General and vocational education thus seemed increasingly out of touch with reality.

5. Conclusion

With respect to model fit, researchers do not seem adequately sensitive to the fundamental reality that there is no true model, and all models are wrong to some degree, even in the population, and that the best one can hope for is to identify a parsimonious, substantively meaningful model that fits observed data adequately well [23]. Given this perspective, it is clear that a finding of good fit does not imply that a model is correct or true, but only plausible. We found model 1 and model 2 acceptable or adequate fit in interpreting the hypothesized relationships. The education factor and its indicators in Malaysia in 1995 didn't affect occupation factor based on both models. This was consistent with the study of Fasih [13], which stated that just increasing the quantity of education at the lower educational levels didn't raise earnings substantially, and thus didn't prove to be effective in helping people climb out of poverty. Education is a necessary but not sufficient condition for an individual to enjoy good labor market outcomes, where good labor market opportunities for the skilled require an economy as a whole to be operating well, with macroeconomic stability, an attractive investment climate, and efficient labor markets. The structures we had reported here as well as the strength of causal path-ways may vary depending on the specific nature and circumstances of the population under study. Further research is required in other developing countries.

References

- [1] E. J. Anderson (1980). Continuing education: A practical approach to career education, k-12, *The Journal of Adventist Education*, 42(2), 17-16.
- [2] J. Angrist, E. Bettinger and M. Kremer (2006). Long-term educational consequences of secondary school vouchers: Evidence from administrative records in Colombia, *American Economic Review*, 96(3), 847-862.
- [3] F. Barrera-Osorio (2007). *The impact of private provision of public education: Empirical evidence from Bogotá's concession schools*, Policy Research Working Paper No. 4121, World Bank, Washington, DC.

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- [4] P. M. Bentler (1980). Multivariate analysis with latent variables: Causal modeling, *Annual Review Psychology*, 31, 419-456.
- [5] O. Bertrand (1994). *Education and work*, International commission on education for twenty-first century, UNESCO, Paris. Available online at http://www.unesco.org/education/pdf/16_53.pdf
- [6] D. Blane, E. Brunner and R. Wilkinson (1996). *Health and Social Organization: Towards a Health Policy for the Twenty-First Century*, Routledge, London.
- [7] K. A. Bollen (1989). *Structural Equations with Latent Variables*, John Wiley & Sons, New York.
- [8] K. A. Bollen, J. L. Glanville and G. Stecklov (2001). Socioeconomic status and class in studies of fertility and health in developing countries, *Annual Review of Sociology*, 27(1), 153-185.
- [9] T. Chandola, P. Clarke, D. Blane and J. N. Morris (2005). Pathways between education and health: A causal modeling approach, *Journal of the Royal Statistical Society Series A*, 169, 337-359.
- [10] F. Chung (1993). *Education, work and employment*, paper prepared for the International Commission on Education for the Twenty-First Century.
- [11] D. De-Ferranti, F. M. William, E. P. Guillermo, G. J. Indermit, G. Luis, S. P. Carolina and S. Norbert (2003). *Closing the Gap in Education and Technology (Latin American and Caribbean Studies)*, World Bank, Washington, DC.
- [12] M. E. Duper (2008). Educational differences in health risks and illness over the life course: A test of cumulative disadvantage theory, *Social Science Research*, 37(4), 1253-1266.
- [13] T. Fasih (2008). *Linking Education Policy to Labor Market Outcomes*, World Bank, Washington, DC.
- [14] A. Field (2000). *Structural equation modeling (SEM)*, 1-9. Available online at <http://www.sussex.ac.uk/users/andyf/teaching/pg/sem.pdf>
- [15] J. F. Hair, R. E. Anderson, R. L. Tatham and W. G. Black (1998). *Multivariate Data Analysis* (5th ed.), Prentice Hall International, Englewood Cliffs, NJ.
- [16] G. Hazarika (2001). The sensitivity of primary school enrollment to the costs of post-primary schooling in rural Pakistan: A gender perspective, *Education Economics*, 9(3), 237-244.

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- [17] L. Hu and P. M. Bentler (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives, *Structural Equation Modeling*, 6(1), 1-55.
- [18] K. Jöreskog and D. Sörbom (1982). Recent developments in structural equation modeling, *Journal of Marketing Research*, 19(4), 404-416.
- [19] K. Jöreskog and D. Sörbom (2001). *LISREL8: User's Reference Guide* (2nd ed.), SSI, Lincolnwood, IL.
- [20] R. B. Kline (1998). *Principles and Practice of Structural Equation Modeling*, Guilford Press, New York.
- [21] O. Kravdal (2008). A broader perspective on education and mortality: Are we influenced by other people's education? *Social Science and Medicine*, 66, 620-636.
- [22] H. M. Levin and R. W. Rumberger (1989). Education, work and employment: Present issues and future challenges in developed countries, In F. Caillods (Ed.), 121-145, *The Prospects for Educational Planning. A Workshop Organised by IIEP on the Occasion of Its 25th Anniversary*, UNESCO/International Inst. for Educational Planning, Paris.
- [23] R. C. MacCallum and J. T. Austin (2000). Applications of structural equations modeling in psychological research, *Annual Review of Psychology*, 51, 201-226.
- [24] Malaysia, Department of Statistics (1995). *Population Report for Administrative Districts*, Department of Statistics, Kuala Lumpur, Malaysia.
- [25] M. L. Nordstrom, S. Cnattingius and B. Haglund (1993). Social differences in Swedish infant mortality by cause of death, 1983 to 1986, *American Journal of Public Health*, 83, 26-30.
- [26] T. Raykov, A. Tomer and J. R. Nesselroade (1991). Reporting structural equation modeling results in psychology and aging: Some proposed guidelines, *Psychology and Aging*, 6, 499-503.
- [27] C. E. Ross and C. Wu (1995). The links between education and health, *American Sociological Review*, 60, 719-745.
- [28] A. Rwomire (1992). Education and development: African perspectives, *Prospects*, 22, 227-239.
- [29] D. Smith and K. Langfield-Smith (2004). Structural equation modeling in management accounting research: Critical analysis and opportunities, *Journal of Accounting Literature*, 23, 49-86.

- [30] A. Von Borstel (1991). A theoretical framework for productive education, *Prospects*, 22, 265-271.
- [31] A. Wanger (2006). *Measuring up internationally: Developing skills and knowledge for the global knowledge economy*, 1-31, National Center Report, National Center for Public Policy and Higher Education. Available online at <http://www.highereducation.org/reports/muint/index.shtml>
- [32] World Bank (2002). *Pakistan poverty assessment; poverty in Pakistan: Vulnerabilities, social gaps and rural dynamics*, Report No. 24296-PAK, Washington, DC.
- [33] World Bank (2006). *World development report 2007: Development and the Next Generation*, World Bank, Washington, DC.